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Tools for transport: Driven to learn with connected vehicles

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Abstract

Vehicle automation and assistance technologies have been touted as a means by which to reduce traffic collisions by minimizing or eliminating “error-prone” and inefficient human operators. In concept, automation exists on a continuum that includes engaged driving by a human operator augmented by automated support features, vigilant driver monitoring of vehicle behavior with the possibility of driver take-over, to full automation with no active monitoring by a human operator. Moreover, the degree of automation varies by vehicle features (e.g., lane centering, emergency braking, adaptive cruise control, parking), by setting, meaning that automated features may or may not be available depending on specific attributes of the traffic environment (e.g., traffic volume, road geometry, etc), and by implementation (e.g., haptic vs auditory warnings). Thus, these automotive “transportation tools” are highly heterogeneous and pose unique challenges and opportunities for driver training. In this paper, we report the results of an experimental study ($n=36$) to determine if enhanced vehicle feedback influences driver trust, effort, frustration, and performance (indexed by reaction time) in a virtual driving environment. Results are contextualized in the extant literature on learning to operate motor vehicles and outline key research questions essential for understanding the processes by which skilled performance develops with respect to a real-world practical tool: the increasingly automated automobile.

Tools for transport: Driven to learn with connected vehicles

The automobile is a tool like no other. The early 1900s saw mass production of the Ford Model T, which had wide-ranging effects on the transportation of people, goods, and services that has fundamentally changed nearly every aspect of human life. While vehicle technology has evolved over time, the disruptive force of autonomous passenger vehicles cannot be understated. The automation of passenger vehicles has been touted as a means by which to reduce traffic collisions by minimizing, or completely eliminating, “error-prone” and inefficient human operators. In concept, automation exists on a continuum that includes engaged driving by a human operator augmented by automated support features, vigilant driver monitoring of vehicle behavior with the possibility of driver take-over, to full automation with no active monitoring by a human operator. Moreover, the degree of automation varies by vehicle features (e.g., lane centering, emergency braking, adaptive cruise control, parking), by setting, meaning that automated features may or may not be available depending on specific attributes of the traffic environment (e.g., traffic volume, road geometry, etc.), and by implementation (e.g., haptic vs auditory warnings). Thus, these automotive “transportation tools” are highly heterogeneous and pose unique challenges and opportunities for driver training. In this paper, using a cognitive science perspective, we outline the extant literature on learning to operate a motor vehicle and then critically review the emerging literature on learning to operate vehicles with automated features – advanced driver assistance systems (ADAS). Then, using exemplar data extracted from an experimental study conducted using a virtual reality driving paradigm, we illustrate how enhanced collision warnings can affect driver performance. These results are then discussed in the greater context of tool use and skilled learning focusing on the adoption and utilization of mental models.

In the broadest sense, operating a motor vehicle is simply using a machine to get from one location to another. The automobile itself (i.e., one large tool) consists of a variety of sub-tools,

including the steering wheel, gearshift, dashboard displays, and signaling apparatus to name just a few examples. Indicators of driver performance are commonly conceptualized as behavioral errors, regulatory violations, self-reported attentional lapses, and judgment errors (de Winter & Dodou, 2010; Michon, 1985). Cognitive indicators of performance largely are derived from behavioral and eye tracking studies that measure drivers' responses to hazards through button presses, hard braking, and eye glance fixations (e.g., response latencies, errors) (Crundall, 2016; McDonald et al., 2015; Underwood et al., 2002). More recently, naturalistic driving studies utilizing continuous or semi-continuous data recorders have been used to measure vehicle kinematics (Dingus et al., 2016). Crash-involvement and associated risk factors can be ascertained by all of these approaches with the addition of administrative data sources (e.g., police reports, hospital admissions) (Curry et al., 2019; Montella et al., 2013).

Most of the research on learning to drive is conducted with young people who are seeking licensure for personal transportation purposes. Evidence is clear that young, novice drivers are overrepresented in crash databases and traffic injury is a leading cause of death for this age group (WISQARS, 2020). Professional drivers (e.g., motorsport) or commercial drivers (e.g., taxi drivers) already know how to drive prior to taking up a driving related profession. The research on young drivers indicates that population-level crash rates are highest immediately following licensure, then decreases rapidly over the first 6 months with younger age being associated with higher peak rates at the point of licensure (Curry et al., 2015). Learner drivers appear to acquire the physical mechanics (i.e., maneuvering and basic perceptual awareness) necessary for operating a vehicle relatively quickly, but some continue to have difficulty with more dynamic traffic scenarios. For example, a systematic on-road observational study found that learner young drivers made more basic vehicle operation errors (e.g., changing lanes, turning) than licensed adult drivers, but overall vehicle operation errors were uncommon, accounting for less than 10% of errors in both groups of drivers (Durbin et al., 2014). Notably, in this same study,

54% of learner young drivers made at least one critical error compared to only 5% of adult drivers. The most common critical error was unsafely entering oncoming traffic for drivers of both groups. This experience pattern is consistent with analyses of crash databases; crash scenarios of young drivers mirror those of adults (e.g., recognition errors) (McDonald et al., 2014) suggesting that when people of different age groups crash they do so for largely similar reasons, but younger drivers crash more frequently per mile driven.

ADAS are an engineering solution to the driver error problem, and are designed to prevent drivers from making errors that can increase their crash risk through advanced warnings (e.g., auditory or haptic feedback of an approaching or potential hazard), or by taking control of the vehicle (e.g., mechanical lane keeping assist). Notably, some ADAS features best serve driver comfort (e.g., adaptive cruise control or ACC) rather than safety (Viti et al., 2008). The spectrum from fully manual to fully automated has been defined by SAE International to segment the functions and layers of features of automated systems into 6 levels (SAE Standard, 2018). From manual driving (Level 0), the general progression from 1 to 5 allows the driver to drive feet-off with the help of ACC (Level 1), hands-off with the help of a lane keep assist (Level 2), eyes-off with a more advanced automated driving system (Level 3), mind-off with a highly automated driving system (Level 4), and finally driverless with a fully autonomous system (Level 5). Overly publicized demonstrations aside, there are currently no vehicles available on the market above SAE level 2 (Teoh, 2020).

Introduction of ADAS-equipped vehicles will not serve as an immediate panacea. While ADAS features were available on 92.7% of 2018 new vehicles in the U.S., these features were not universally offered as standard, with features such as automatic emergency braking costing on average an additional cost of \$1,896 and as much as \$6,000 (AAA, 2019). Such safety “premiums” may be cost-prohibitive for some of the most at-risk drivers should they be able to purchase a new car. Often drivers have used vehicles that do not have the most recent safety

features and technologies onboard (Eichelberger et al., 2015). An examination of fatal crash data from 2019 reveals that 55% of the vehicles were 11 or more years old, with 13% being 21 years or older (Fatality Analysis Reporting System (FARS), 2020). The situation is more concerning in examining young (i.e., 15-20 years old) driver-involved fatal crashes, revealing 59% of the vehicles involved were 11 or more years old (FARS, 2020). Given the lag in standard features and slow vehicle turnover, it may take decades for full market penetration to personal vehicles, with introduction to commercial fleets first and followed by higher-end personal vehicles.

How drivers learn to operate an ADAS-equipped vehicle is an emerging and important literature (Jenness et al., 2019). This issue is most relevant for situations when the driver must continue to monitor the traffic environment for safety threats (Kaber, 2018). Drivers' mental models, that is, their ideas about how the ADAS functions, influence their ability to use ADAS properly (Pradhan et al., 2020). ADAS misuse can include failure to interpret the meaning of notifications, not being aware of notifications, and more critically not knowing when to override it (Onnasch et al., 2014; Victor et al., 2018). Relatedly, the extent to which operators trust the system will also influence their ability to use it effectively (Hancock et al., 2020).

The limited literature on learning to use ADAS is predominantly survey-based (Abraham et al., 2018); however, behavioral studies are increasing. These studies have indicated that although benefits of ADAS are observable such as with crash avoidance systems (Jermakian, 2011), so are opportunities for misuse, especially among younger drivers with comparatively little practical driving experience (Bao et al., 2020). Misuse, in part, appears to stem from a lack of an accurate mental model (Endsley, 2000). Inaccurate mental models of ADAS technology may be exacerbated by lack of driving experience, specifically when a large subset of ADAS functions requires an accurate understanding of the driving task environment. Alternatively, novices' "blank canvas" might facilitate uptake of ADAS functionality, as there is no prior mental model

that it has to compete with, avoiding interference or negative transfer effects. Experimental research that involved providing different types of instruction (e.g., written, multimedia) has not reliably been shown to be successful towards increasing the accuracy of mental models or reducing ADAS misuse among adult experienced drivers (Noble et al., 2019). Further, drivers' perceptions about the amount of effort to use ADAS and their subjective experience of its use (e.g., degree of frustration) will all influence uptake of ADAS-equipped vehicles. The degree of overlap between the functions of the ADAS and the properties of the driving environment, along with their downstream effects on mental workload, should determine whether driving experience affects ADAS comprehension.

To study this issue further we re-analyzed data from a previously conducted evaluation of connected vehicles technology (Jenness et al, 2014) to determine how ADAS can affect driver performance and their subjective experience. Our purpose was to determine if vehicle-provided feedback could indicate to the driver that a threat was present *and* that it has ceased to be a potential danger (i.e., it has been resolved). Other research on adaptive cruise control has demonstrated that repeated trials with accurate feedback have improved mental models and trust in the automation (Beggiato et al., 2015; Beggiato & Krems, 2013) along with aspects of behavioral performance (Forster et al., 2019) in longitudinal studies. Event resolution feedback may be particularly useful in situations where an initial warning was provided, but through no act of the driver, it was resolved. These resolutions could happen when another motorist resolves the threat on their own for just one example. Such scenarios could be confusing to the driver because they a) took no action to resolve the threat and/or b) may not have seen the threat to begin with, despite the warning, and thus mistakenly interpret the initial warning as a false alarm. Without a resolution notification, drivers may learn to expect similar “faux false alarms” which may lead to slowed responses (e.g., braking, steering) to subsequent warnings, and increased frustration and effort, reduced trust, and an inaccurate mental model.

Overall Design Summary

A between-group experimental study design determined if an enhanced vehicle notification system improved drivers' safety behaviors without reducing trust and without increasing effort and frustration. The secondary study objective was to determine if there was effect modification based on driver experience. Participants were randomly assigned to one of two simulated driving conditions, *Threat Resolution*, within which drivers drove a vehicle and received collision threat warnings followed by threat resolution notifications, and *Warning Only*, within which drivers received only collision threat warnings and no resolution notifications. Thus, the independent variable was notification type (warning only or warning plus threat resolution) and the four dependent variables for this analysis were drivers' time to first response following the threat warning (response time), self-reported effort, frustration, and system trust.

We hypothesized that the threat resolution group would demonstrate: (1) safer driving performance as indexed by response time (RT) (e.g., quicker RTs) and (2) higher levels of trust. We made no a priori hypothesis about effort and frustration; these analyses should be considered exploratory. Similarly, for the second objective concerning effect modification by driver experience, we made no a priori hypothesis.

Participants

Thirty-six participants (18 males and 18 females) between the ages of 18 to 30 years old ($M = 24.1$, $SD = 3.6$) were recruited to participate in this four session study using convenience sampling methods. Participants were screened to ensure they had at least two years of licensed driving experience (minimum of 4,000 miles driven per year), normal or corrected-to-normal vision (20/40 or better), normal color vision, no apparent cognitive limitations, and no history of motion sickness. The years since licensure ranged from 2 to 16 years ($M = 7.9$, $SD = 3.6$) across all participants. The sociodemographic characteristics of the sample were Threat

Resolution: Gender: 8 female, 10 male; Age: $M = 23.56$ ($SD = 3.6$); Years Licensed: $M = 7.1$ ($SD = 3.4$) and Warning Only: Gender: 9 female, 9 male; Age: $M = 24.56$ ($SD = 3.5$); Years Licensed $M = 8.6$ ($SD = 3.9$).

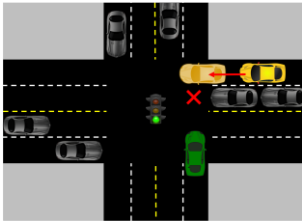
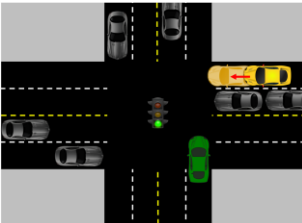
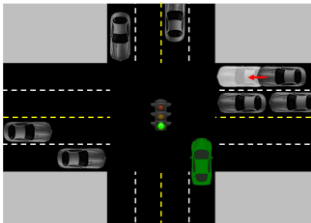
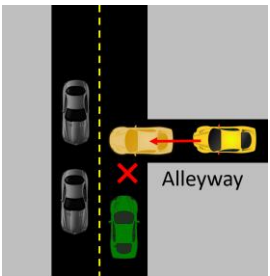
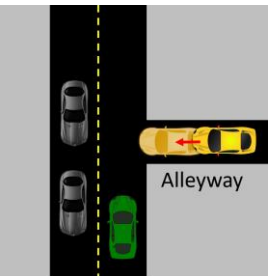
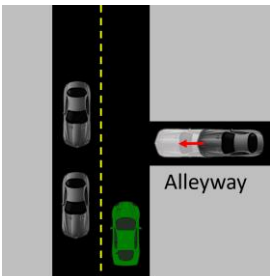
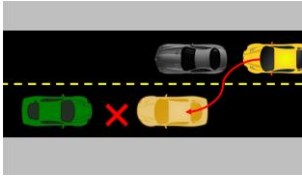
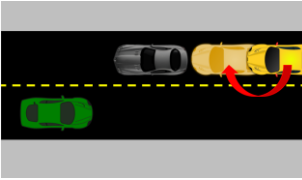
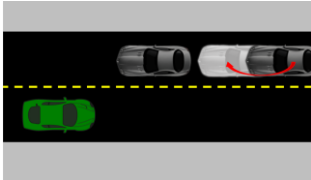
The participants were categorized based on the number of years licensed in order to explore effects related to experience. Participants who had 2 to 6 years as a licensed driver were in a *lower experience* (novice) category ($n = 15$), those with 7 to 11 years of experience as a licensed driver were in an *intermediate experience* category ($n = 15$), and those with 12 to 16 years of experience were in a *higher experience* (*experienced*) category ($n = 6$).

Materials and Measures

The study was conducted in a partial motion-based driving simulator manufactured by Realtime Technologies, Inc. The simulator consisted of a 2002 Saturn SC2 full vehicle cab featuring realistic control operation and instrumentation including power assist for the brakes and force feedback for the steering. Haptic feedback was provided by car body vibration and a three-axis electric motion system producing roll, pitch and yaw motion within a limited range of movement. Auditory feedback was provided by a 3D surround sound system. The driving environment in this simulator was projected to a five-channel, 210-degree forward visual field screen (2.5 arc-minutes per pixel) with rear and side mirror views provided by a rear screen and vehicle-mounted LCD panels, respectively.

The simulated worlds consisted of an urban, relatively cluttered environment with storefronts, office buildings, and parked and moving distractor vehicles. The urban world featured two- and four-lane streets with multiple signalized and unsignalized intersections. Each urban world consisted of twenty-five 200 meter blocks (via four lane streets) and twenty 100 meter blocks (via two lane streets) and was composed of approximately 44 intersections and two turns. The critical events were created such that they afforded a high level of face-validity.

All drivers were presented with warnings for various scenarios in which a critical situation either resolved (i.e. no crash must be avoided) or occurred (i.e. were visually verifiable and a crash must be avoided). Resolved events were either visually verifiable (i.e. the driver saw the reason for the warning) or non-verifiable (i.e. drivers did not see the reason for the warning). Examples of the scenarios are shown in Table 1.

Table 1. Event scenarios			
Event Description	Critical Event Type		
	Occurred: Visually Verifiable	Resolved: Visually Verifiable	Resolved: Non-verifiable
Frontal Conflict at intersection			
Frontal Conflict at Alleyway			
Frontal Collision head-on			

Note: The salient green and gold cars indicate the participant's vehicle and potential threat vehicle, respectively, at the event start. The faded gold and gray cars indicate the threat vehicle's progression through the event. Gray cars denote non-threat vehicles. The red "x" indicates where a collision or near collision is likely to occur.

Collision Notification

The initial warning tone for both groups consisted of an audio warning that was produced through a sound server attached to a 3-D enhanced sound system, such that a warning sound appeared to originate from the direction of the conflict vehicle (e.g., left). The sound was identical to Sound #8 in the CAMP project (Kiefer et al., 1999). This was a 2.1 second tone with peaks at 2500, 8000 and 12000 Hz. The audio warning was presented at 83 dB, while the ambient traffic measured 77.5 dB maximum. The visual warning was provided by three sets of red LED lights placed at different locations within the vehicle (see Figure 1). When activated, the LEDs flashed at 4-Hz rate with a 50% duty cycle (125 ms on, 125 ms off), for a total duration of 2.125 seconds.

Insert Figure 1 Here

Both audio and visual components were directional, i.e., only one side of the interior speakers sounded and only one set of the LEDs flashed indicating the direction from which the conflict vehicle was arriving. The tone and LEDs were presented for 1.7 sec.

Threat Resolution Notification

In the Threat Resolution condition, the tone was suspended for .034 sec., resumed at a lower intensity, then rapidly decreased for .130 sec., and decreased at a slower rate for 1.65 sec., lasting a total of 1.8 sec. (see Figure 2 for a visual depiction of the waveform); the resolution signal was uni-modal (i.e. auditory only).

Insert Figure 2 Here

Procedures

Following informed consent and randomization, participants completed two 6-minute practice drives to become familiar with the simulator, driving tasks, warnings (and resolution feedback, if applicable) and were presented with three seen non-critical conflict events with warnings. Next, they were instructed to drive through a simulated urban environment over the course of 4 sequential driving sessions. Each session had two drives, each lasting 10 minutes. Within each drive, participants were presented with an average of 5 warning events (i.e., 4 to 6 events) throughout each drive of each session (i.e., 10 total events presented in each session). The events were presented in fixed order and contained a balance of right angle, head-on, and rear-end crashes or near-crashes across each session. For the purpose of the current study, only the first drive was relevant for the stated hypotheses.

Participants were told to observe the speed limit (i.e. 30 mph), complete the route in a safe and timely manner, and avoid potential collisions. Threat warnings presented to drivers coincided with one of three conflict events: a colliding vehicle (occurred, visually verifiable event), a critically approaching vehicle which halts in the view of the driver (resolved, visually verifiable event), and a halting vehicle out of the view of the driver (resolved, visually unverifiable event). The proportion of these events varied across the four sessions as follows: Session 1: 100% occurred: visually verifiable; Session 2: 60% occurred: visually verifiable, 40% resolved: visually verifiable; Session 3: 33% occurred: visually verifiable, 33% resolved: visually verifiable, and 33% resolved: non-visually verifiable; and Session 4: 20% occurred: visually verifiable, 20% resolved: visually verifiable, 60% resolved: non-visually verifiable. See Table 1 for reference of event types.

Dependent Variables

Reaction time was measured in seconds from the warning onset to the first initiation of a braking or steering response within a 3.5 sec window. Anticipatory responses (i.e., less than 250 ms from the initiation of the critical action of the threat vehicle) were excluded from the analyses.

Trust, effort, and frustration were measured at the conclusion of each session. Trust was measured by System Trust Questionnaire with four categories, each an average of two scales, identified by Lee and Moray (1992). The trust scales measured perceptions of Performance (i.e., expectation of consistent/desirable performance), Process (i.e., qualities governing system), Purpose (i.e., underlying system motives), and Foundation (i.e., system's adherence to social order), see Rakauskas et al., (2003). Measures of effort and frustration were derived from two of six individual scales from the NASA-RTLX (Byers et al., 1989).

Participants were remunerated for their participation at a rate of \$20/hour. The total time to complete the study was approximately four hours. The study protocol was approved by the University of Minnesota Institutional Review Board under study number 1206S16365.

Analysis Plan

To evaluate our primary and secondary objectives we fit a multilevel model for first reaction time with fixed effects of Experience (lower, intermediate, higher), Condition (warning only, warning and threat resolution), and Session (1, 2, 3, 4) (experience and session were treated as categorical factors), and by-subject random intercepts and session slopes. Degrees of freedom for fixed effect estimates were based on Satterthwaite approximation.

Results

A main effect for condition was observed such that drivers who received the warning and resolution indicators had faster reaction times than drivers in the warning only condition: Estimate -0.12, $SE = 0.052$, $t(35.5) = 2.34$, $p = 0.025$ (Figure 3). There was no main effect or

interaction by driver experience on reaction time. Effects of experience were not significant based on model comparisons, i.e., did not improve model fit (main effect: $\chi^2(2)=1.04$, $p>0.5$; $\chi^2(2)=1.04$, $p>0.5$; interaction: $\chi^2(2)=1.25$, $p>0.5$; $\chi^2(2)=1.25$, $p>0.5$). Further, there was no main effect of condition (all $p>0.15$) and no interactions between session and condition (all $p>0.15$) on any of the measures of trust, frustration and effort.

There was a main effect for Session for Trust Process ($\chi^2(3)=17.5$, $p<0.001$), Trust Purpose ($\chi^2(3)=17.8$, $p<0.001$), Effort ($\chi^2(3)=34.0$, $p<0.0001$), and Frustration ($\chi^2(3)=33.7$, $p<0.0001$) such that Frustration was higher in earlier sessions and both measures of Trust were higher in later sessions; please see Table 2 and Figure 4. A correlation matrix is presented in Table 3 illustrating the relationships among the dependent variables (e.g., negative associations between frustration and trust).

Exploratory data visualizations were generated to examine patterns in session 4 trust by condition and experience (Figure 5). Session 4 was selected because participants in both groups would have had maximum exposure to all the critical events and have full experience with the warning system(s). The groupings were as follows (Threat resolution: novice = 9, intermediate = 7 and experienced = 2; warning only condition: novice = 6 intermediate = 8 and experienced = 4).

Insert Figure 3 Here
Insert Figure 4 Here
Insert Figure 5 Here

Table 2. Average [Mean(SD)] Self-reported effort, frustration and trust by condition and session

	Session	Effort	Frustration	Trust Foundation	Trust Performance	Trust Process	Trust Purpose
Resolution	1	68.89 (17.65)	54.06 (24.21)	76.47 (14.51)	67.33 (16.79)	64.36 (20.39)	74.75 (13.98)
Warning Only	1	62.78 (17.50)	54.44 (24.95)	78.50 (10.71)	68.14(20.93)	76.39 (16.87)	79.56 (15.11)
Resolution	2	57.72 (22.53)	37.67 (19.59)	77.75 (12.36)	66.94 (19.08)	73.53 (13.00)	75.11 (15.29)
Warning Only	2	53.56 (20.09)	37.17 (20.89)	78.53 (13.35)	67.28 (17.76)	77.92 (12.82)	77.69 (15.09)
Resolution	3	47.89 (28.02)	33.50 (22.46)	79.75 (13.46)	67.42 (21.92)	74.53 (18.25)	76.50 (15.28)
Warning Only	3	44.39 (24.13)	37.72 (26.19)	79.58 (10.36)	64.06 (20.60)	78.94 (13.49)	82.22 (11.69)
Resolution	4	49.22 (28.55)	30.89 (24.29)	80.50 (11.12)	70.58 (23.69)	78.67 (15.77)	81.47 (13.92)
Warning Only	4	43.06 (25.36)	33.78 (29.36)	79.97 (13.20)	68.33 (21.10)	81.56 (13.31)	86.08 (9.65)

Note: Resolution = Threat Resolution

Table 3. Correlation matrix of dependent variables.

	First RT	Effort	Frustration	Trust Foundation	Trust Performance	Trust Process	Trust Purpose
First RT	-						
Effort	.024	-					
Frustration	.054*	.639***	-				
Trust Foundation	-.004	-.174***	-.023	-			
Trust Performance	-.030	.067*	-.090***	.408***	-		
Trust Process	-.067**	-.090**	-.063*	.571***	.702***	-	
Trust Purpose	-.054*	-.115***	-.154***	.557***	.517***	.607***	-

Note. Pearson r correlations, controlling for subject. Analyzes all events. * < .05, ** < .010, *** < .001

Discussion

In the present study, we evaluated how a resolution tone in conjunction with a collision warning compared with a collision warning only condition on driver performance, effort, frustration, and trust. Then, we evaluated if these associations differed by driver experience. The results indicated that the enhanced ADAS condition with the resolution tone was associated with faster reaction times. This main effect did not differ in strength according to driver experience suggesting that the enhanced warning and resolution system was equally beneficial irrespective of the amount of experience drivers' had acquired previously; however, the study was not powered to test interactions between experience and condition. Further, there was not strong evidence that the resolution warning by itself adversely affected drivers' subjective experiences related to their trust of the system, their experience of frustration, or their perception of effort.

Although the results showed no main effect for experience on reaction time, we further explored the question of experience as it relates to trust by plotting drivers' session four ratings of trust, by condition and by level of driving experience. Our rationale for focusing on session four ratings of trust was that participants would have had full exposure to the ADAS across the maximum number of simulated critical events and because it had the greatest number of non-visually verifiable, but resolved, critical events (60%). Visual inspection of these data indicated an emerging pattern. Ratings of trust performance and trust process, and to a lesser extent trust purpose, showed that experienced drivers in the resolution notification condition reported stronger trust (performance, process) compared with experienced drivers in the warning only condition, but the opposite pattern was observed for novice drivers. Ratings of trust foundation were equivalent among novices in both conditions but higher among experienced drivers in the resolution condition compared with the warning only condition.

These results suggest the potential for there being an interaction between driver experience, warning type, and some dimensions of trust, in particular drivers' expectations of consistent and desirable performance and trust in the underlying qualities governing the system. It seems that the resolution tone may have helped experienced drivers understand that an unseen event was resolved (i.e., it made an unknown hazard a known and resolved hazard). For this cognitive process to work effectively, it may require a more sophisticated understanding of the traffic environment such that experienced drivers: a) are not just focusing on what is directly observable to them, b) understand that their perspective is fallible and limited in certain contexts and situations, and c) have developed a more advanced "transportation theory of mind" so that they understand that other road users are capable of having a different perspectives and knowledge states than the driver's own (i.e., another road user might perceive a hazard and resolve it before the novice driver perceives the same hazard and/or resolves it).

Critically, our study was not powered to evaluate these interactions statistically so these results should be interpreted with caution and only in the context of informing avenues for future research in order to establish the robustness and size of these effects. Indeed, prior research, albeit using different methodology, found that novices demonstrated difficulty with ADAS (Bao et al., 2020). It is our interpretation that this overall pattern of data is indicative of the acquisition of a more accurate mental model of how the ADAS functions facilitated by the warning resolution system, but that prior experience may affect drivers' trust in new systems. Notably, sessions varied by both their order and the composition of event types, and thus future research should be conducted to unpack the relative contributions of practice quantity (i.e., greater exposure overall) and practice diversity (e.g., exposure to a variety of events) towards performance and trust over time.

Outside of the ADAS literature, the individual-level psychological and behavioral countermeasures with the strongest potential for crash reduction among novice drivers is direct

or indirect facilitation of the acquisition of cognitive strategies for reducing risk, improved visual search being one such strategy (Fisher et al., 2006). Mechanistically, strategy acquisition (i.e., implicit or explicit adoption of an action-motor plan to reduce crash risk) likely happens quickly and non-linearly through phase transitions due to person-environment interactions (Mirman, 2019; Mirman et al., 2019). Although the phase transition framework is consistent with other research on skilled behavioral performance (Gray & Lindstedt, 2017), it departs from the widely held but not empirically supported view that young drivers' post-license reductions in crash risk, and hence learning to drive, happens gradually (McCartt et al., 2003; Simons-Morton & Ehsani, 2016).

A thorough review of the learning to drive literature in conjunction with a computational cognitive modeling analysis of two rigorous field trials and over 10 million crash-involved young drivers from three different countries did not find empirical support for gradual learning processes. It did provide support for discontinuity in learning to drive processes with phase transition timings and antecedents differing across drivers (Mirman et al., 2019). Evidence is also accumulating that diversity of learner drivers' experience also appears to be a crucial component for facilitating drivers' safe and appropriate vehicle use. An experimental study found that practice diversity is feasible to change through intervention and that greater diversity protected novices from making critical driving errors (Mirman et al., 2014). Observational studies have also indicated the potential benefit of distributed practice (Ehsani et al., 2020), but suffer from self-selection bias and lack of comparison conditions.

Research connecting these two bodies of literature together, ADAS and learning to drive, is still in its infancy. Using a phase transition framework may be one avenue for bridging them. In so much that having an accurate mental model is critical for appropriate ADAS use, it will be essential to know how to expedite drivers' acquisition of those models. The Phase Transition Framework for learning to drive can be applied for this purpose. The PTF has three core

postulates focused on changes in crash risk: (1) changes in crash risk are abrupt, and occur at different times for different drivers; (2) person-environment interactions can cause an immediate phase transition, or increase the probability of a future phase transition; and (3) there is substantial heterogeneity of risk in the population (Mirman, 2019). Adapted for ADAS mental models, the acquisition of mental models could be substituted for crash risk such that (1) acquisition of the mental models and their constituent parts is abrupt and not gradual; (2) person-environment interactions can cause rapid adoption of a mental model or the probability of its adoption, and (3) there is substantial heterogeneity in drivers' ADAS-related mental models. A new extension would postulate (4) that a partial mental model would be insufficient for consistently safe and effective ADAS use.

With respect to this final postulate, (i.e., the importance of knowing if a mental model is constructed gradually or incrementally) it is useful to recall that an incremental model of learning to drive has historically been the dominant view of how drivers learn. That is that drivers gradually accumulate an experience library, access of which is automatized through repetition (Simons-Morton & Ehsani, 2016). It is also useful to note that although this is an intuitive theory there is a lack of direct empirical evidence that this is the case among learning drivers with respect to any type of driver performance (e.g., crash rates, proxies of risky driving) (Mirman et al., 2019). If using a tool correctly is dependent on an accurate mental model of how that tool works, it is crucial then for understanding if mental models are constructed and accessed gradually or in a phased manner. In the context of mental model acquisition at its simplest level, we are considering if drivers build their mental model bit by bit and ADAS use becomes incrementally better in lockstep or they have a fuzzy, or otherwise incomplete understanding until a phase transition happens and the model's boundaries and attributes rapidly come into focus. With respect to use of a mental model, it may be that an 80% accurate mental model is enough to use ADAS correctly, but a 79% accurate mental model is not (quantities were chosen

arbitrarily for illustration purposes). Further, the content of the particular inaccuracy may also be relevant. If the inaccuracy involves a rarely encountered use case it might not matter that often if the mental model is insufficiently complete; however, if it is a frequently encountered use case that missing detail might be devastating.

The extent to which learning to use ADAS systems corresponds to a power law model of learning has been explored in a few studies focused on evaluating how drivers learn adaptive cruise control (ACC). Self-reported trust, acceptance and self-reported learning of ACC functionality were evaluated in an experimental study over 10 trials and showed some support for a power law learning pattern (Beggiato et al., 2015). However, goodness of fit metrics for the power law function were not consistent or strong and ranged from a high of only $R^2=.73$ for “knowing what the ACC messages mean” to a low of $R^2=.13$ for “knowing overall ACC functionality.” Similarly, model fit statistics for Acceptance was only $R^2=.15$ and Trust only $R^2=.44$. These same patterns held for the disaggregated, individual-level data. Of note, Beggiato et al., 2015 also described the data as “stabilizing” and in the case of “overall functionality” as being high immediately after an initial training. Neither of these observations are consistent with a power law of learning: a) learning rates slow, but they do not stop; and b) learning rates are faster initially but do not jump qualitatively higher after an initial training and would not differ in their timing of learning onset for one facet of learning but not for another. Both leaps/phase changes, differences in learning onset, and stabilization are consistent with phase transition models of change (Gray & Lindstedt, 2017; Mirman, 2019). While evidence for mental model development (i.e., increase in accuracy) was found as experience with the ACC system increased, these data were collected at fewer, unequally spaced intervals and not subjected to a model fit evaluation for power-law processes as were the trust, acceptance, and self-reported learning data (see Beggiato et al., 2015). Another study, albeit with only 6 trials, found much stronger fits with power law functions $R^2>.97$ for ACC learning indexed by gaze transitions to

critical regions of interest (i.e., scanning efficiency) and self-report (Forster et al., 2019). Similar to the Beggiato et al., 2015 study, mental model change data were presented to illustrate that task experience increases mental model accuracy, but were not evaluated with a power law function (or any learning model) and the authors noted a learning plateau, which is not consistent with a power law of learning model.

Adjudicating between learning frameworks will be a useful path forward because it can improve basic theory about learning to use tools, and ADAS in particular, which can then lead to improved ADAS design and ADAS training programs. For example, under a power law of learning model one would be focused on expediting learning rates and providing a greater number of safe training opportunities as opposed to trying to manipulate phase transition timing, perhaps by changing the salience of stimuli in the environment.

With respect to our study on threat warnings and resolution notifications, future research can be conducted to independently manipulate quantity and diversity of event exposures to determine if and how they contribute to the development of mental models, how those models are constructed and used (i.e., if they follow a power law or phase transition pattern), if they lead to appropriate ADAS use, and consequently affect driver safety. Practically, it is not possible to discriminate between a power law of learning function and the beginning of a phase transition function (e.g., evaluated with a sigmoid for example) without many more units of observation than included in any of these studies; see Mirman 2019 for a detailed description of how to evaluate phase transition claims with respect to driver behavior and learning. Therefore, study designs need to be thoughtfully developed with the understanding that there is not one universal model of tool learning and further that different types of ADAS might follow different types of learning models and frameworks.

Finally, in our study we did not find strong support for differences in ADAS effectiveness based on prior driving experience. It could be that we needed a bigger sample and range of experience or that the richness and accuracy of the driving mental model did not really inform the participant about the functioning of the ADAS. Put another way, it is still unclear how much a driver really needs to know about driving to know that one sound means the ADAS thinks a collision is imminent and a resolution sound means everything is okay. We did observe some initial evidence that instances of unseen but resolved hazards may be harder to understand for novices than for experienced drivers. An addition of a resolution indicator may be especially useful to help drivers discriminate between a false alarm and an unseen but resolved event with the caveat that novices might need additional support interpolating information about unseen hazards and understanding system notifications. Collectively, these results indicate that the warning and resolution system increased appropriate “tool use”, resulting in safer driver behavior as indexed by faster reaction times for all driver types.

Automation that is more complex may really require deep understanding of the task environment to develop a fully accurate mental model of the automated system. More highly automated systems of the future (i.e., SAE level 3/4) may meet similar issues of loss due to poor mental models if systems are designed to conservatively cue the driver to resume manual control well ahead of a necessary handoff, and these may be particularly problematic for novices. Such cuing may not be met with an actual handoff (i.e., critical situation resolved) and thus may be perceived as a system malfunction followed by slower response times. These two domains (driving and the collision warning/threat resolution ADAS) may be mostly independent; thus future research should consider how models develop based on driver experience in greater specificity.

Reference

- American Automobile Association (2019). Advanced driver assistance technology names: AAA's recommendation for common naming of advanced safety systems. Retrieved from: <https://www.aaa.com/AAA/common/AAR/files/ADAS-Technology-Names-Research-Report.pdf>
- Abraham, H., Reimer, B., & Mehler, B. (2018). Learning to Use In-Vehicle Technologies: Consumer Preferences and Effects on Understanding. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 62(1), 1589–1593. <https://doi.org/10.1177/1541931218621359>
- Bao, S., Wu, L., Yu, B., & Sayer, J. R. (2020). An examination of teen drivers' car-following behavior under naturalistic driving conditions: With and without an advanced driving assistance system. *Accident Analysis & Prevention*, 147, 105762. <https://doi.org/10.1016/j.aap.2020.105762>
- Beggiato, M., & Krems, J. F. (2013). The evolution of mental model, trust and acceptance of adaptive cruise control in relation to initial information. *Transportation Research Part F: Traffic Psychology and Behaviour*, 18, 47–57. <https://doi.org/10.1016/j.trf.2012.12.006>
- Beggiato, M., Pereira, M., Petzoldt, T., & Krems, J. (2015). Learning and development of trust, acceptance and the mental model of ACC. A longitudinal on-road study. *Transportation Research Part F: Traffic Psychology and Behaviour*, 35, 75–84. <https://doi.org/10.1016/j.trf.2015.10.005>
- Byers, J. C., Bittner, A., & Hill, S. (1989). Traditional and raw task load index (TLX) correlations: Are paired comparisons necessary. In A. Mital (Ed.), *Advances in industrial ergonomics and safety I* (pp. 481–485). London, UK: Taylor & Francis.
- Crundall, D. (2016). Hazard prediction discriminates between novice and experienced drivers. *Accident Analysis & Prevention*, 86, 47–58. <https://doi.org/10.1016/j.aap.2015.10.006>

- Curry, A. E., Pfeiffer, M. R., Carey, M. E., & Cook, L. J. (2019). Catalyzing traffic safety advancements via data linkage: Development of the New Jersey Safety and Health Outcomes (NJ-SHO) data warehouse. *Traffic Injury Prevention, 20*(sup2), S151–S155. <https://doi.org/10.1080/15389588.2019.1679552>
- Curry, A. E., Pfeiffer, M. R., Durbin, D. R., & Elliott, M. R. (2015). Young driver crash rates by licensing age, driving experience, and license phase. *Accident Analysis & Prevention, 80*, 243–250. <https://doi.org/10.1016/j.aap.2015.04.019>
- de Winter, J. C. F., & Dodou, D. (2010). The Driver Behaviour Questionnaire as a predictor of accidents: A meta-analysis. *Journal of Safety Research, 41*(6), 463–470. <https://doi.org/10.1016/j.jsr.2010.10.007>
- Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences, 113*(10), 2636–2641. <https://doi.org/10.1073/pnas.1513271113>
- Durbin, D. R., Mirman, J. H., Curry, A. E., Wang, W., Fisher Thiel, M. C., Schultheis, M., & Winston, F. K. (2014). Driving errors of learner teens: Frequency, nature and their association with practice. *Accident Analysis & Prevention, 72*, 433–439. <https://doi.org/10.1016/j.aap.2014.07.033>
- Eichelberger, A. H., Teoh, E. R., & McCartt, A. T. (2015). Vehicle choices for teenage drivers: A national survey of U.S. parents. *Journal of Safety Research, 55*, 1–5. <https://doi.org/10.1016/j.jsr.2015.07.006>
- Endsley, M. R. (2000). Situation Models: An Avenue to the Modeling of Mental Models. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 44*(1), 61–64. <https://doi.org/10.1177/154193120004400117>

- Ehsani, J. P., Gershon, P., Grant, B. J., Zhu, C., Klauer, S. G., Dingus, T. A., & Simons-Morton, B. G. (2020). Learner driver experience and teenagers' crash risk during the first year of independent driving. *JAMA pediatrics*, 174(6), 573-580.
- Fatality Analysis Reporting System (FARS)*. (2020). NHTSA. <https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars>
- Fisher, D. L., Pollatsek, A. P., & Pradhan, A. (2006). Can novice drivers be trained to scan for information that will reduce their likelihood of a crash? *Injury Prevention*, 12(suppl 1), i25–i29. <https://doi.org/10.1136/ip.2006.012021>
- Forster, Y., Hergeth, S., Naujoks, F., Beggiato, M., Krems, J. F., & Keinath, A. (2019). Learning and Development of Mental Models during Interactions with Driving Automation: A Simulator Study. *Proceedings of the 10th International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design: Driving Assessment 2019*, 398–404. <https://doi.org/10.17077/drivingassessment.1724>
- Gray, W. D., & Lindstedt, J. K. (2017). Plateaus, Dips, and Leaps: Where to Look for Inventions and Discoveries During Skilled Performance. *Cognitive Science*, 41(7), 1838–1870. <https://doi.org/10.1111/cogs.12412>
- Hancock, P. A., Kajaks, T., Caird, J. K., Chignell, M. H., Mizobuchi, S., Burns, P. C., Feng, J., Fernie, G. R., Lavallière, M., Noy, I. Y., Redelmeier, D. A., & Vrkljan, B. H. (2020). Challenges to Human Drivers in Increasingly Automated Vehicles. *Human Factors*, 62(2), 310–328. <https://doi.org/10.1177/0018720819900402>
- Jenness, J. W., Baldwin, C., Chrysler, S., Lee, J., Manser, M., Cooper, J., Salvucci, D., Benedick, A., Huey, R., Robinson, E., Gonzales, C., Lewis, B., Eisert, J., Marshall, D., Lee, J., Morris, N., & Becic, E. (2014). Connected vehicles DVI design research and distraction assessment (DRAFT). Unpublished technical report.
- Jenness, J., Lenneman, J., Benedick, A., Huey, R., Jaffe, J., Singer, J., & Yahoodik, S. (2019). Spaceship, Guardian, Coach: Drivers' Mental Models of Advanced Vehicle Technology.

- In C. Stephanidis (Ed.), *HCI International 2019—Posters* (pp. 351–356). Springer International Publishing. https://doi.org/10.1007/978-3-030-23525-3_46
- Jermakian, J. S. (2011). Crash avoidance potential of four passenger vehicle technologies. *Accident Analysis and Prevention*, 43(3), 732–740. Scopus.
<https://doi.org/10.1016/j.aap.2010.10.020>
- Kaber, D. B. (2018). Issues in Human–Automation Interaction Modeling: Presumptive Aspects of Frameworks of Types and Levels of Automation. *Journal of Cognitive Engineering and Decision Making*, 12(1), 7–24. <https://doi.org/10.1177/1555343417737203>
- Kiefer, R., LeBlanc, D., Palmer, M. Salinger, J., Deering, R. and Shulman, M. (1999). Development and Validation of Functional Definitions and Evaluation Procedures for Collision Warning/Avoidance Systems (Final Report DOT HT 808 964). Washington, DC: National Highway Traffic Safety Administration.
- Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. *Ergonomics*, 35(10), 1243-1270.
- McCartt, A. T., Shabanova, V. I., & Leaf, W. A. (2003). Driving experience, crashes and traffic citations of teenage beginning drivers. *Accident Analysis & Prevention*, 35(3), 311-320.
- McDonald, C. C., Curry, A. E., Kandadai, V., Sommers, M. S., & Winston, F. K. (2014). Comparison of teen and adult driver crash scenarios in a nationally representative sample of serious crashes. *Accident Analysis & Prevention*, 72, 302–308.
<https://doi.org/10.1016/j.aap.2014.07.016>
- McDonald, C. C., Goodwin, A. H., Pradhan, A. K., Romoser, M. R. E., & Williams, A. F. (2015). A Review of Hazard Anticipation Training Programs for Young Drivers. *Journal of Adolescent Health*, 57(1, Supplement), S15–S23.
<https://doi.org/10.1016/j.jadohealth.2015.02.013>

- Michon, J. A. (1985). A Critical View of Driver Behavior Models: What Do We Know, What Should We Do? In L. Evans & R. C. Schwing (Eds.), *Human Behavior and Traffic Safety* (pp. 485–524). Springer US. https://doi.org/10.1007/978-1-4613-2173-6_19
- Mirman, J. H., Curry, A. E., Winston, F. K., Wang, W., Elliott, M. R., Schultheis, M. T., ... & Durbin, D. R. (2014). Effect of the teen driving plan on the driving performance of teenagers before licensure: A randomized clinical trial. *JAMA pediatrics*, 168(8), 764-771.
- Mirman, J. H. (2019). A dynamical systems perspective on driver behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, 63, 193–203. <https://doi.org/10.1016/j.trf.2019.04.010>
- Mirman, J. H., Curry, A. E., & Mirman, D. (2019). Learning to drive: A reconceptualization. *Transportation Research Part F: Traffic Psychology and Behaviour*, 62, 316–326. <https://doi.org/10.1016/j.trf.2019.01.010>
- Montella, A., Andreassen, D., Tarko, A. P., Turner, S., Mauriello, F., Imbriani, L. L., & Romero, M. A. (2013). Crash Databases in Australasia, the European Union, and the United States: Review and Prospects for Improvement. *Transportation Research Record*, 2386(1), 128–136. <https://doi.org/10.3141/2386-15>
- Noble, A. M., Klauer, S. G., Doerzaph, Z. R., & Manser, M. P. (2019). Driver training for automated vehicle technology – knowledge, behaviors, and perceived familiarity. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 63(1), 2110–2114. <https://doi.org/10.1177/1071181319631249>
- Onnasch, L., Wickens, C. D., Li, H., & Manzey, D. (2014). Human performance consequences of stages and levels of automation: An integrated meta-analysis. *Human Factors*, 56(3), 476–488. <https://doi.org/10.1177/0018720813501549>
- Pradhan, A. K., Pai, G., Radadiya, J., Knodler, M. A., Fitzpatrick, C., & Horrey, W. J. (2020). Proposed framework for identifying and predicting operator errors when using advanced

- vehicle technologies. *Transportation Research Record*, 2674(10), 105–113.
<https://doi.org/10.1177/0361198120938778>
- Rakauskas, M., Ward, N., Shankwitz, C., & Donath, M. (2003). System performance and human factors evaluation of the driver assistive system (DAS): Supplemental track test evaluation. Retrieved from the University of Minnesota Digital Conservancy, <https://hdl.handle.net/11299/785>.
- SAE International Standard, “Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles” SAE Standard J3016_201806, Rev. Jun. 018.
- Simons-Morton, B., & Ehsani, J. P. (2016). Learning to drive safely: reasonable expectations and future directions for the learner period. *Safety*, 2(4), 20.
- Teoh, E. R. (2020). What’s in a name? Drivers’ perceptions of the use of five SAE Level 2 driving automation systems. *Journal of Safety Research*, 72, 145–151.
<https://doi.org/10.1016/j.jsr.2019.11.005>
- Underwood, G., Crundall, D., & Chapman, P. (2002). Selective searching while driving: The role of experience in hazard detection and general surveillance. *Ergonomics*, 45(1), 1–12.
<https://doi.org/10.1080/00140130110110610>
- Victor, T. W., Tivesten, E., Gustavsson, P., Johansson, J., Sangberg, F., & Ljung Aust, M. (2018). Automation expectation mismatch: incorrect prediction despite eyes on threat and hands on wheel. *Human Factors*, 60(8), 1095–1116.
<https://doi.org/10.1177/0018720818788164>
- Viti, F., Hoogendoorn, S. P., Alkim, T. P., & Bootsma, G. (2008, June). Driving behavior interaction with ACC: results from a Field Operational Test in the Netherlands. In 2008 IEEE Intelligent Vehicles Symposium (pp. 745-750). IEEE.
- WISQARS (*Web-based Injury Statistics Query and Reporting System*)|*Injury Center*|CDC. (2020, July 1). <https://www.cdc.gov/injury/wisqars/index.html>